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Chapter 9: Data Governance, Trust, and Responsible AI Operations

9.1 Introduction

An organization generates and collects vast amounts of data on a daily basis through day-to-day operations: supplier and customer transactions; labor operations; website access; digital marketing; product and equipment usage; and online and internal communications. However, many organizations do not have data governance policies or organizational structures to ensure that these vast amounts of data are organized and secure; comply with relevant laws and regulations; are of sufficient quality; can be used in a timely manner; and can be exposed to users, departments, and systems that have the appropriate rights. Data within organizations needs to be managed like other organizational assets in order to derive value, yet it is often viewed and managed as a by-product of other operations. The lack of data management processes can lead to issues, such as excessive time spent searching for information, difficulties in ensuring compliance with privacy regulations, poor product quality, inability to meet customer needs, security breaches, and, more seriously, costly fines and loss of reputation, key customers, and business.

The operations and development of AI systems present additional challenges and considerations. AI systems are increasingly being incorporated into a wide range of applications, products, and services in many organizations. However, there have been multiple high-profile incidents involving AI systems that have caused considerable monetary damages and significant reputational harm. These issues, along with the power and influence of such systems, have led to calls for the use of trustworthy AI—AI systems that respect and adhere to established, trusted ethical principles within the organization, and are socially acceptable within society. Additionally, regulations governing the development and use of AI systems have started to emerge, and AI risk assessment and management frameworks are now being developed.

9.1.1. Background and Significance

Regulators around the world have proposed or implemented new laws and regulations requiring companies to provide individuals more control of their data. The EU General Data Protection Regulation (GDPR) mandates within certain boundaries that organizations provide consumers access to their data, delete such data if requested, and notify impacted parties when data breaches happen. Similarly, the California Consumer Privacy Act (CCPA) grants Californians the right to know what personal information is being collected about them, to whom it is being shared, and the right to delete such information.

The proposed European Digital Services Act regulations, if signed into law in their present form, will require Internet-based platforms to explain algorithms to users. Companies must maintain an audit trail of recommendation processes, making data-readable and enabling successful third-party verification and scrutiny. Failure to comply could mean hefty fines or force the closure of an online service. Such regulation is not restricted to Europe. Similar proposals are being reviewed in Canada, the UK, and elsewhere. The US Congress is also studying different proposals to enhance consumer protection in the digital arena, including data governance provisions within the consumer-protection domain.

Fig 9.1: Data Governance, Trust, and Responsible AI Operations

9.1.2. Research design

To investigate data governance, trust, and responsible AI operations, the author reviewed a diverse range of industry and academic sources, focusing on studies in the fields of information systems, operations management, data science, AI, ethics, software engineering, and human–computer interaction. These contributions were complemented by practical AI case studies, frameworks from consultancies, and insights from AI risk management in highly regulated industries. The analysis culminated in a synthesis of themes, key themes, and facets, followed by the specification of metrics and their associated benchmarks.

The resulting design is depicted in the form of a matrix that captures the three lines of accountability for data governance and the structure for trust in AI systems. Each data governance line corresponds to the key focus areas of data stewardship and ownership, data quality, lineage, and metadata, and access, privacy, and compliance, while trust in AI systems covers trustworthy AI principles, AI risk management and accountability, and the roles of explainability and transparency in fostering user trust. Responsible AI operations are structured around operationalizing responsible AI, monitoring, evaluation, and feedback loops, and auditing, certification, and continuous improvement.

9.2. Foundations of Data Governance

Data stewardship lays the foundation of effective data governance by establishing accountability for its management. Critical questions include determining who is responsible for which data, to what extent, and how that is guaranteed. Data ownership defines the ultimate responsibility and accountability for the data. Owners are typically business leaders, while custodial roles are assigned to those in charge of day-to-day management. Defining custodial roles is particularly important when internal lines of ownership and responsibility are blurry, such as for data related to enterprise architecture. Applying an organizational RACI matrix clarifies decision rights with regard to data governance.Foundations of Trust in AI Systems.

Managing data involves various ongoing responsibilities comparable to those of a landlord. The land is owned by others, but it is cared for by those with custodial responsibility. They can be found by asking: How does your area of the organization use this data? Who do you call when you have a question about this data? Who is responsible for assuring the quality of this data? If any of these people do not act as a landlord should, they are holding the data hostage.

9.2.1. Data Stewardship and Ownership

Effective data governance necessitates clear allocation and documentation of ownership, custodianship, and stewardship of data sources. Data owners are ultimately responsible for creating and approving data quality standards, determining, and enforcing access controls, overseeing compliance with relevant laws and regulations, and maintaining preparedness for audits and assessments. The joining of operational and commercial expertise with data-ethical leadership makes the owner ideally positioned to determine how the data quality dimensions apply to their domains of responsibility. For data in commercial use, this oversight can usually be delegated to a trusted external data steward or custodian. Data custodianship, assigned for proprietary or sensitive noncommercial data, is a technical role typically concerned with maintaining data quality and regulatory readiness.

In practice, custodians are assisted in this work by data and systems engineers, although ownership for the broader custodianship responsibilities remains with the data custodian. Roles should be formally assigned in a responsibility assignment (RACI) matrix or similar document, with additional accountability lines defined in escalation and escalation procedures. Cross-functional approval of challenging or sensitive distribution requests is recommended. Any labels or tags applied to the data during these requests should be acknowledged and assessed for enhancement during regular feedback loops with the data users.

9.2.2. Data Quality, Lineage, and Metadata

Data Quality, Lineage, and Metadata

Business processes depend on data, but if that data is inaccurate, defective, incomplete, or inconsistent, the resulting information and knowledge are also flawed. Thus, data quality is paramount. Quality dimensions are specific features of data that describe their quality. For example, it is widely recognized that the quality of any dataset can be assessed by examining the following dimensions: completeness, consistency, accuracy, timeliness, and validity. Managing data quality involves regular monitoring, maintenance, and scorecarding of these dimensions, potentially leveraging artificial intelligence or machine learning techniques for automation. Strategies from the fields of data management, data governance, business intelligence, and data analytics guide this task.

Business processes also often depend on data lineage information, particularly in highly regulated industries such as finance and healthcare, which require regulatory compliance. To ensure compliance, organizations must provide visibility into how data is sourced and transformed from its source to its final destination, helping to answer questions such as, “Where did this data come from? How was it transformed? Are the data provisions in our privacy policies honored? Are we using consulted data correctly?” The business processes executed by organizations evolve constantly, making it necessary to track and update lineage information continuously. Metadata additionally aids in the effective formulation, execution, and management of data-related business processes by providing descriptive data about objects stored electronically in any data repository. Such information can include evidence regarding the completeness, accuracy, and consistency of the items of interest, together with knowledge of the relationships between all the described data entities. Metadata repositories also contain meaningful content describing the objects within repositories. Thus, the effective management of metadata also constitutes a crucial aspect of data governance decision-making.

9.2.3. Access, Privacy, and Compliance

Controlled access is core to a data governance framework. It defines who can access which data, under which conditions, achieving the principle of least privilege without hindering business operations. Access rights must be enforced through technical means and periodically validated. Data governance also establishes foundations for privacy and compliance management. Privacy-preserving techniques, such as anonymization or differential privacy, are principles and standard practices for privacy-protecting data sharing. Legal requirements, such as those of the General Data Protection Regulation, must be documented and followed in daily operations.

Data governance sets organizational standards for sharing and reusing customer data. Such data may be shared by commercial departments and business units with external providers. Data-sharing agreements help ensuring that the purpose of cross-organizational sharing complies with contractual regulations for customer data. A cross-border transaction should respect the nationality of the customer and the disclosure agreement. Data ownership is not effective in data-sharing scenarios, but a cross-border transaction requires rightly set roles in a cross-border transaction scenario.

9.3. Trust in AI Systems

To build decision-making trust or confidence in AI systems, organizations are increasingly utilizing AI risk management frameworks that operationalize trustworthy AI principles and allow AI risk to be evaluated similar to other technology risks. Doing so requires organizations to establish a common understanding of what constitutes an AI system, what the risks associated with the use of AI systems are, and how to evaluate those risks as part of the organizations’ broader risk management processes. For AI systems that are not classified as low risk, such as those that generate outputs likely to substantially impact people's lives or that process sensitive data, organizations are embracing the concept of AI explainability. AI explainability is related to the comprehension of the cause-and-effect chain of a particular model's prediction by a wide audience including practitioners, business and domain experts, and end-users.

Four main groups of principles underpin the realization of trustworthy AI: ethical, legal and regulatory responsible AI; resilient by design; explainable AI; and human-AI interaction. These principles support AI governance objectives around trust, compliance, and responsible AI operations and should resonate with the organization's values. To provide decision-makers with the confidence needed to trust the outputs of AI systems and make important business decisions, organizations should compile risk information at multiple levels of detail throughout the risk management process.

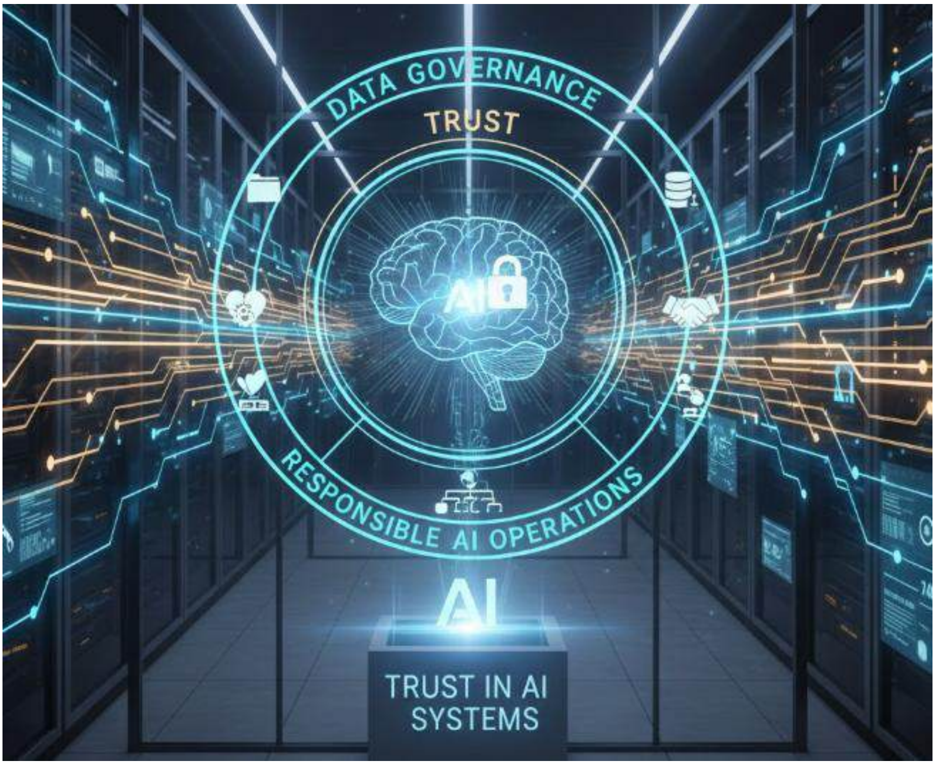

Fig 9.2: Trust in AI Systems

9.3.1. Trustworthy AI Principles

Principles of Trustworthy AI include safety, reliability, privacy, and security, which align with the goals of Data Governance. Embedding these principles within the objectives of Data Governance and Governance Everywhere helps ensure that the remaining elements of Trust do not become bullet points, but rather, are mechanisms for enabling the successful delivery of AI within Trust. Furthermore, the principles of Trustworthy AI must reflect the ethical considerations when deploying AI and ML solutions for an organization and fundamentally articulate that AI must be built and used responsibly.

The Corporate Governance Framework for AI proposes that organizations adopt a risk management framework for AI Systems to understand the scope of risks and liability associated with them. Some risks, such as regulatory risk, reputational risk, and financial risk, can be inherent in all Corporate Governance Frameworks. Beyond Risk, liability considerations propel the necessity for line ownership for AI Systems both through the AI development lifecycle and subsequent operations. The Governance Model for AI lends itself to standardization and strives for a consistent approach to AI development and deployment.

9.3.2. AI Risk Management and Accountability

AI operations imply consistently building, deploying, using, monitoring, communicating, and evaluating AI systems in a responsible manner. This requires assessing their risk exposure with an enterprise Risk Management Framework and defining Accountability at an appropriate level. Globally recognized AI development principles emphasize the importance of mitigating undesirable outcomes. AI systems create a risk profile in relation to other processes, products, and services of the organization, as well as by themselves. Categories of risks inherent in an AI system are Reputation, Safety, Compliance, Environment, Business Continuity, Privacy, Ethical, Operational, Cyber, Fraud, and Human Resources. Organizations should ideally assess Risk for AI-enabled Products/Services in one shot during the scope definition for different processes of the project.

Every organization's risk exposure should be evaluated using the respective MI and Governance frameworks of the country. A typical Risk Management Framework for AI-enabled Products/Services has five main facets: Scope, Assessment, Management Plan, Validation, and Communication. The responsibility for AI operations does not lie solely with the AI Governance Board but is defined at every level of the organization. Organizations may have separate criteria for AI operations Risk Management or align with their standard Risk Management and control mechanisms. These efforts can be amplified by linking AI systems to the Enterprise Risk Management initiative of the organization.

9.3.3. Explainability, Transparency, and User Trust

Although specific explanation methods for artificial intelligence systems and processes are still being developed, it is clear that user trust depends on the successful balancing of several factors. A more transparent model presents a lower cognitive burden, as users are less likely to have to guess how the system will behave in any particular situation, and chances are that its responses will be less surprising. Transparency will thus positively impact trust. However, transparency is not sufficient for trust. Underlining the effect of transparency, research shows that transparent policy-based systems are trusted more when the policy is straightforward and adheres to common sense; conversely, a complex policy makes them more mistrusted. An explanation provided by an interpretable, intrinsically understandable model can ameliorate or compensate for lack of transparency, and the effect of offering an explanation even increases when the model is used for more critical tasks.

A trusting interaction can be achieved through progressively revealing more information during user interactions. Users accept gradually revealed complex behavior, rather than specifying a rule for every case. Users are generally more tolerant of ambiguous actions by a less understood intelligent agent than they are of ambiguous actions by an agent that is more understood. Trust is also affected when complaints about the intelligent agent are made without a corresponding increase in emotion.

9.4. Responsible AI Operations

Responsibly developed and deployed AI is often used to refer to models that are fittingly trained in a manner that adheres to responsible development principles outlined in previous sections of the exposition. However, a more stringent definition would suggest that the term should extend to include not just these principles targeted at development and validation but the complete operating model employed by companies as they shift AI from development into long-term production in their operations. A mature operational model should identify and define the workstreams and deliverables that encompass the complete life-cycle operation from human:=driven data annotation through operational model retraining to displacement of legacy data products. While the perceived immediacy to scale the initial deployment through a thin responsible AI oversight model has been seen as pragmatic, the longer-term development and operational scale resources need to be integrated into a comprehensive and sustainable operational view of responsible AI operation. Producing a set of workflows, evidenced decision rights, governance gates and associated material into a cohesive operational model enables the model to scale to meet growing demand, incorporate the learning feedback loops needed to enhance accuracy and utility, along with providing assurance that it is fit-for-purpose for the higher-risk deployment use cases.

9.4.1. Operationalizing Responsible AI

Developing and deploying AI systems entails a range of decisions that require balancing trade-offs: optimizing a marketing algorithm’s return on investment while mitigating the risk of unfair discrimination, for example. Instituting operational procedures, decision rights, and governance gates can help decision makers recognize and respond to such trade-offs. First, the key decisions that affect the responsible use of AI should be identified. This can be achieved, for instance, through a framework that maps the full AI lifecycle and highlights where decisions could breach trust-related principles or risks. The framework can be supplemented with RACI matrices that clarify who is informed, consulted, and accountable for responsible decision making in specific AI-related contexts. On the operational side, explicit checkpoints can help evaluate whether an AI initiative is achieving its intended purpose and whether it is experiencing unintended consequences. Governance bodies can then integrate operational feedback into their oversight responsibilities, adjusting decision rights and governance gates accordingly. Integrating responsible AI principles and practices into an organization’s day-to-day operations should help accelerate the scaling of trustworthy AI and avoid lengthy implementation delays.

Operationalizing responsible AI requires defining procedures, decision rights, and governance checkpoints to enable organizations to respond to trade-offs and unintended consequences in a structured manner. The goal is to integrate responsible AI considerations into the daily activities of teams developing, deploying, and using AI systems so that these systems can be scaled at speed and volume. Achieving this goal entails examining the key decisions that affect the responsible use of AI, mapping them against frameworks for responsible AI adoption, identifying necessary check-ins and approvals, and embedding decision rights and governance gates into the operationalization workflow.

9.4.2. Monitoring, Evaluation, and Feedback Loops

Monitoring of AI models is critical to ensure they operate within accepted boundaries and deliver intended business benefits. Some risks are continuously monitored (e.g., model performance). Others are checked periodically (e.g., data drift) or selectively (e.g., fairness and explainability are investigated for high-risk decisions). Monitoring metrics should be consistent with risk factors defined in the risk assessment and mitigation plan, integrated into the governance workflow, and executed by the AI steward responsible for the relevant model. Too much information can lead to alert fatigue and inaction, so it is advisable to prioritize indicators. The monitoring cadence should be clearly documented in an evaluation strategy—no surprises for the stewards operating the models.

The evaluation feedback loop provides a mechanism for learning from experience and seeking opportunities for improvement. Monitoring and evaluation should be linked to organizational learning objectives. How effective is the learning process? Is valuable information from monitoring and evaluation being actioned? How can the evaluation process be improved? These questions can be addressed in a padlet or similar shared space for open reflection. Key items warranting deeper consideration over time can be captured in a dedicated audit for continuous improvement.

9.4.3. Auditing, Certification, and Continuous Improvement

Audit standards and certification schemes, either internally devised or externally sourced, are vital for elucidating the examination process of AI systems. Consequently, a well-articulated examination standard paired with a clear-cut process for overcoming weaknesses reinforces and substantiates the verification of trustworthy AI systems. For instance, the ACT framework developed by Trustworthy AI@TUM encompasses a triadic evaluation terrain: assessment, certification, and testing. Crafted primarily for the external assessment and certification of AI systems, the framework also accommodates internal evaluations — albeit in a less precise manner — while additionally providing a testing blueprint that covers aspects vital for the technical and ethical soundness of AI systems.

Continuous improvement hinges on employing dedicated metrics that gauge the organizational readiness of AI, as well as the monitoring of newly deployed, mature, and non-functional systems. These metrics should factor into a broader, periodic evaluation employing carefully devised experimental designs. Such evaluations not only support external auditing, but also grand organizations the opportunity to expand their empirical inventory on AI systems, thereby acquiring factual knowledge to substantiate further implementations.

9.5. Governance, Roles, and Organizational Alignment

Governance structures need to define who is accountable for trustworthy and responsible AI. Data governance should incorporate AI stakeholders who check for data, decision, processing, and performance risks. The interdependencies between AI and cybersecurity require close linkages between AI and security committees and CISO offices. Moreover, establishing a responsible AI committee involving business units, information security, risk management, and compliance functions ensures that workflows integrate responsible AI decision points with other business operations. Policies should delineate the decision rights and escalation paths for developers, validation teams, business stakeholders approving the models, and post-implementation monitoring teams.

Cross-department responsibilities need to be clearly defined to ensure that work is carried out and evaluated effectively. A simple RACI matrix of people and departments involved in the lifecycles shows who is involved in a task, who supports and makes recommendations, who decides the outcome, and who performs the task. This matrix may heavily involve the privacy and information security functions because of the importance of ethical and privacy issues in responsible AI development. The preference should be to have an RACI breakdown for all line of business–centric tasks rather than leaving roles completely unwritten, which can be fertile ground for blame games, finger-pointing, and unfocused activity. Stakeholder engagement and ethics review processes need to ensure that developers of AI systems in business units and functions such as cybersecurity, compliance, risk, and privacy are kept informed and appropriately consulted, while enabling an accelerated implementation process.

Fig 9.3: Governance, Roles, and Organizational Alignment

9.5.1. Governance Structures and Policies

Data governance can take many forms in different organizations, depending on size, complexity, structure, and sector. Regardless of its specific formal configuration, however, a data governance framework must define the governing body and its subcommittees, the relevant policies and standards, and the overall decision rights and escalation mechanisms. The overall governance structure provides decision rights for data-related investments and spending, aligns data-related strategic initiatives and priorities across functions, and communicates governance-related decisions throughout the organization. Data governance also ensures that AI systems comply with laws, regulations, and internal policies at every operational gate and that data-related investments support mission-critical business and risk management objectives. By considering these components of governance together, organizations can adopt an integrated yet tailored approach to governing data proliferation and supporting the responsible use of data for AI.

All organizations that strive to adopt Responsible AI should consider implementing a data governance framework. Risk management functions are especially likely to benefit from a data governance infrastructure that provides increased visibility into risk-relevant data. However, simply building a data governance framework does not guarantee effective, holistic oversight of data risk. For organizations of all sizes, care must be taken to define policies governing risk-related data, map appropriate governance roles and committees, clarify decision rights, and articulate escalation paths. Together, these components enable the establishment of a governance framework that aligns investments in risk-related data and data pipelines with enterprise priorities and enables consistent, responsible use of data in support of mission-critical risk management initiatives.

9.5.2. Roles, Responsibilities, and Cross-Functional Collaboration

Collaborative data governance enables organizations to identify and assign responsibilities for the various components of trustworthy AI management. Critical functions do not neatly map to a single department or role; for example, communication with affected stakeholders typically spans research, product, operations, and communications teams. Also, a fully resourced Communications team may not be equipped to handle unexpected situations arising from algorithms in production. To clarify where each team contributes and, especially, where multiple teams intersect, an RACI (responsible-accountable-consulted-informed) matrix for each potentially impactful application can be a powerful tool.

Employing RACI matrices enables clarification of overlapping responsibilities, especially between Research and Product teams. While Government Affairs often owns the overall narrative for organization-level Responsible AI communication because of their deep ties to external regulators, these messages need to be customized for each AI program. Affected users of powerful AI applications may be consulted through user-testing and focus-group mechanisms, often located in Design teams or community organizations. Curriculum and learning design for AI UpSkilling programs may be driven by dedicated teams outside of Product, but product builders will be closely engaged throughout the process. Such consultative engagement prepares the organization to address inevitable voices of skepticism and concern about the application.

9.5.3. Stakeholder Engagement and Ethics Review

Strategic stakeholder engagement fosters inclusive dialogue that informs decision-making, prioritizes outreach to those affected by and capable of shaping AI initiatives, and translates into ethical action. Stakeholder engagement processes should be employed whenever the impacts of intended or deployed systems extend beyond the confines of an organization. These can include discussion forums to identify acceptance criteria, definition of user requirements for new or updated systems, or any procedure through which key stakeholders provide feedback.

Formal ethics reviews allow organizations to align systems with clearly articulated values while identifying potential risks, unintended consequences, and areas for improvement. These reviews are best performed by a group that possesses both technical AI knowledge and ethical understanding. A predefined checklist can help the review remain focused; it should address the actual deployment impacts of specific AI products and services. Further stakeholder engagement can assist organizations in defining ethical values, determining their implications for AI initiatives, and identifying safeguards against probable infringement. Such values are often modeled on principles outlined in well-known statements from official bodies and private companies, but they must be tailored for effective implementation.

9.6. Conclusion

The synthesis rounds out the analysis of data governance, trust, and responsible operations in Artificial Intelligence (AI) with emergent trends, such as the increasing integration of human-centered design standards in AI model development processes; a corresponding need for supplementary Evaluation and Effectiveness Testing of AI models beyond conventional Performance Testing against a defined use case; greater focus on explainability and interpretability, especially for Human-in-the-loop AI systems; AGI; emerging regulation for adtech; and AI-related digital risk ecosystem management. Identification of these trends reveals gaps in researcher understanding of the present and future roles of these components of Data Governance and Data Asset Management and therefore provides the foundation for future research into these emerging areas of Data Governance, with forward-looking consideration of their impact on government policy, government practice, and state and territory-level Research Ethics Committees.

Data Governance, Trust, and Responsible AI Operations also provide an important basis for the economic performance of organizations leveraging AI technologies—indeed, optimization of the use of these technologies is impossible without accountability and sustainable practices. Trustworthy and responsible adoption of these novel technologies, which have become unconventional the moment their widespread use proved harmful and scandalous, is essential to the continued healthy operation of organizations.

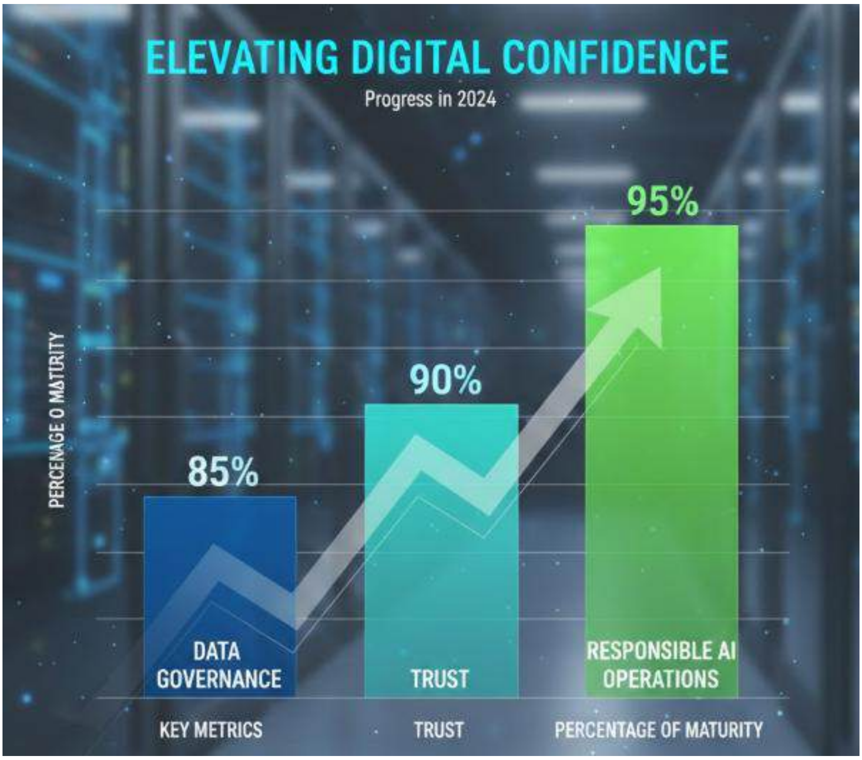

Fig 9.4: Data Governance, Trust, and Responsible AI Operations

9.6.1. Emerging Trends

Several trends will shape the future of data governance, AI trust, and responsible AI operations. Data-fueled organizations will emerge, triggered by the accelerating pace of AI development and usage for business growth. Industry-leading organizations will leverage available data and cutting-edge data technologies—notably cloud-based data lakes, data-as-a-service, and AI-accelerated data pipelines—to fuel AI exploration and scale generative AI products. Consumer-oriented platforms and innovative combinations of diverse data streams will create personalized, relevant experiences for customers on demand and at scale, leading to enhanced loyalty and value capture. The focus on the value of data-as-an-asset and its potential contribution to wealth and return generation for all stakeholders will accelerate investment in data custody, quality, protection, and utilization. Yet, given the nascent status of AI technologies, demand for accountability will emerge as businesses accelerate their AI explorations and investments.

As managers for scrutinized organizations are ever more pressured to demonstrate their AI's beneficial contribution to society, setting the bar for AI implementation higher will require stakeholders to be more confident than ever. Hence, a wider interest in truly trustworthy AI principles and operations is likely to emerge. Organizations will work to ensure their AI is trustworthy—exciting the demand for AI that enhances freedom instead of constraining it, fulfills instead of fabricating, promotes instead of polarizing, empowers instead of desensitizing, explains instead of obscuring, simplifies instead of misleading, and grows instead of defeating honesty. As the trend of operationalizing responsible AI consolidates across industries, early departments engaged in responsible AI operations will introduce measures that mitigate the already identified AI ecosystem risks, systematically track new areas of risk concentration, and increasingly offer frameworks for functional and external third-party audits. Efficient implementation and sustainability at scale will require robust operations, integrated audit standards, certified compliance recognition, and actionable continuous improvement feedback. A lack of independent AI auditing frameworks and a void of recognized foundations for trustworthy AI reinforce the need for adequate, independent, and constructive external scrutiny..

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